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Regional carbon emission performance in China according to a stochastic frontier model

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ABSTRACT

Carbon emissions, per capita carbon emissions, and carbon emissions per unit GDP are traditionally used as indicators of the real carbon emission of a region. However, input variables such as capital and labor and influential factors such as the industrial structure and regional differences are not taken into account in this approach. In this study a trans-log stochastic frontier model is used to develop an index system for measuring regional carbon emission performance that considers relevant input and output variables and influential factors. The main results are as follows: (1) carbon emission performance in China has an upward trend during this period; (2) as proved, among the nation's three major economic regions, in terms of efficiency performance they are ranked in descending order as follows: Eastern China, Central China and Western China; (3) convergence testing shows that there is a convergence trend for carbon emission performance both nationally and for the three major economic regions. Central China has the highest convergence speed and Western China has the lowest.

Contents

1. Introduction

As concern regarding global climate change grows, international authorities have reached a consensus on the development of low-carbon economies. According to International Energy Agency (IEA) statistics, CO_2 emissions in China have exceeded those in the USA since 2007 and China now has the highest carbon emissions worldwide. At the UN 2009 Climate Conference in Copenhagen, China committed to decrease CO_2 emissions per unit GDP by 40–45% by 2020 compared to 2005 levels. The 12th 5-Year Plan for China set a rate of carbon intensity decrease that is 17% lower than that in the 11th 5-Year Plan.

Although both the Tokyo Protocol and the Copenhagen Conference clearly recommended carbon emission reduction obligations for all nations, there is ongoing discussion on how to evaluate national or regional carbon emissions and which indicator to use for scientific measurement. This issue has been explored by many researchers. Mielnik et al. proposed that CO_2 emissions per unit energy could be used as the main criterion to evaluate climate change in economic models for developing countries [1]. According to Ang, the change in energy consumption per unit GDP represents the regional CO_2 emissions [2]. Zhang et al. reported

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that evaluation indices such as the per capita industrialized cumulative carbon emissions and carbon emissions per unit GDP are more likely to be scientific and reasonable [3]. Sun proposed the CO_2 emissions per unit GDP as a good index for measuring decarbonization among countries [4]. Besides the above indicators, per capita carbon emissions indicator is an important measure of the level of regional carbon emissions (RCE) [5,6]. The main indicators for measuring RCE are carbon emissions, per capita carbon emissions, and per unit GDP carbon emissions. However, RCE measurement using these indicators seems too simple. Any realistic emission reduction target needs a comprehensive indicator system comprising economic, social, energy, and environmental factors to measure RCE performance. Some recent studies of carbon emission performance have considered these factors and research methods for resource and environmental efficiency include the total factor approach and data envelopment analysis (DEA) [7].

One problem arises when estimating resource or environmental efficiency via the DEA method: how to deal with pollutants. Production can involve good outputs (GDP), and bad outputs (pollutants). There are two approaches for handling pollutants. In the first, pollutants are considered as undesirable outputs. For example, Chung et al. introduced the radial distance function to construct a new production index model containing desirable and undesirable outputs [8]. Zaim, Zofio, and Zhou evaluated the CO_2 emission performance of OECD countries and other regions at a macro level using different DEA models [9–11]. Wang et al. used a Malmquist index in a DEA model containing undesirable outputs to explore dynamic changes in carbon emission performance (CEP) in China. They also established several models based on environmental production technology to estimate environmental efficiency, economic efficiency, economic environmental efficiency, and two-stage efficiency for different provinces in China [12,13]. Oh and Heshmati constructed a continuous Malmquist–Luenberger productivity index to measure environmentally sensitive productivity considering variable technology and CO_2 emissions [14]. Tu calculated environmental production efficiency to measure the coordination of environmental and industrial growth according to resource inputs, industrial production and environmental pollution data for 30 provinces in China [15]. Zhou et al. built a model based on the Malmqusit index to measure the carbon emission efficiency for 18 countries with the highest global carbon emissions [16]. Lozano and Gutiérrez used a non-parametric frontier approach to model relationships among population, GDP, energy consumption, and CO_2 emissions [17]. The second approach considers pollutants as inputs. For example, Hamid added environmental factors to a production effectiveness function to construct a dynamic agency model to analyze the long-term economic growth rate for optimal policy design [18]. Lu et al. researched sustainable economic development in China under energy and environmental security constraints using energy and carbon emissions as inputs [19]. Ramanathan analyzed the energy and carbon emission efficiency of 17 countries in North Africa according to the DEA method [20]. Hu and Wang defined the total factor energy efficiency as the ratio of the target energy input to the actual energy input according to a variable DEA [21]. Mukherjee estimated the energy efficiency for the six highest energy-intensive manufacturing industries in the USA using DEA [22]. Chen constructed an input–output database for 38 industries and estimated changes in the industrial total factor productivity in China via a trans-log production function and green production accounting [23].

The second approach is used in this study and CO_2 emissions as considered as an input into the SFA model for the following reasons. Firstly, if both energy and CO_2 emissions are used as input indicators, RCE performance may be poorly defined. Secondly, the majority of production activities require an energy input, which leads to CO_2 emissions. So carbon dioxide emissions as component of energy, are introduced as input indicator of the stochastic frontier model. Thirdly, a production frontier always has an environmental effectiveness frontier, whereby environmental technology effectiveness corresponds to the minimum pollutant emissions and the most desirable output. Among environmental efficiency evaluation methods, pollutant emissions should always be minimized, which satisfies the SFA requirement for input indicators.

Methods for evaluating the technical efficiency of decision-making units (DMUs) are divided into parametric and non-parametric approaches. DEA is a parametric method, but it sets boundaries and does not consider measurement errors, which are disadvantages. The stochastic frontier analysis (SFA) method is a parametric approach proposed by Aigner, Battese, and Meeusen [24–26]. SFA considers efficiency measures and stochastic noise affecting a frontier. It estimates the frontier production function via a metering method that measures the efficiency of each DMU and considers a variety of environmental factors that influence their efficiency. Several studies have used SFA to evaluate resource and environmental efficiency. Vaninsky investigated environmental performance in the USA for 1990–2007 using SFA. The frontier comprised GDP, energy consumption, population, and CO_2 emissions indicators expressed as ratios to the total [27]. This indicators design made the Environmental performance scores of DMU be very close, the DMU discrimination was affected, so in this study GDP, CO_2 emissions and other input and output variables are directly from the original value. Du and Zou estimated the carbon emission efficiency for various regions in China from 1995 to 2009 in the SFA framework and analyzed regional differences and influential factors [28]. SFA has also been used to estimate the environmental or technical efficiency of electric utilities (Cuesta et al.; Hattori) [29,30]. From the point of view of production theory Wang et al. proposed a new total factor CO_2 emission performance index using directional distance function followed by stochastic frontier analysis techniques [31]. Reinhard et al. discussed how SFA could be incorporated into DEA. The DEA frontier should be considered as an estimate for the deterministic component of the SFA frontier [32–34]. Instead of this method, a traditional SFA model is used in the present study. In the studies discussed above, except for less literatures efficiency estimation was applied to a closed system without considering the impact of external environmental factors. According to regional systems theory, regional system efficiency is affected not only by the system itself but also by external environmental factors. Results will inevitably be inaccurate if regional system efficiency is only evaluated in terms of the input–output variables for each DMU.

The present study addresses this problem by adding environmental factors to the SFA model. It extends previous research in the following ways: (1) rather than defining CEP from a carbon emission intensity viewpoint or based on the DEA method, CEP is defined in the SFA framework; (2) instead of considering carbon emissions as an undesired output, it is used as an input to explore and improve methods for calculation regional CEP; (3) in calculating CEP, besides input and output variables, environmental factors and random factors are included in the analysis framework to yield more accurate regional CEP data; and (4) convergence testing is applied to investigate the convergence or divergence speed and identify any convergence trends for regional CEP.

The remainder of the paper is organized as follows. Section 2 describes the CEP index constructed based on the stochastic frontier model and associated variables. Section 3 presents and discusses the empirical results. Section 4 concludes this study.

2. Model structure and variable data

2.1. CEP model construction

The SFA method determines frontiers via a production function that assesses DMU efficiency and the impact of disturbances and

other non-efficiency factors by adding environmental factors. The generalized form of the SFA model is as follows:

$$y_{it} = p(x_{it}, t)\exp(v_{it} - u_{it}) \tag{1}$$

where, y_{it} is the actual output of region i in period t, $p(x_{it},t)$ is the output for the highest efficiency, x_{it} is a group of input variables, and $(v_{it}–u_{it})$ is an error term in which v_{it} denotes random disturbances following an $N(0, \sigma_v^2)$ distribution and u_{it} denotes individual shocks following a non-negative-tailed normal distribution $N^+(u, \sigma_u^2)$.

Taking the natural logarithm on both sides of Eq. (1) yields the logarithmic form of the stochastic frontier model

$$\ln y_{it} = \ln p(x_{it}, t) + v_{it} - u_{it} \tag{2}$$

The production function in the stochastic frontier model contains only capital (K) and labor (L). Stiglitz added non-renewable resources (R) to the growth equation to highlight the role of resources in economic growth [35]

$$Y = F(K, L, R, t) = K^{\alpha_1} L^{\alpha_2} R^{\alpha_3} e^{\Phi t} \tag{3}$$

The stochastic frontier model was thus reconstructed as follows for sound estimation of CEP:

$$Y_{it} = A(t) K_{it}^{\alpha} L_{it}^{\beta} C_{it}^{\gamma} \exp(v_{it} - u_{it}) \tag{4}$$

where, C represents CO_2 emissions, α is the elasticity for capital output, β is the elasticity for labor output, and γ is the elasticity for carbon emissions output. Miller ignored the assumption that the elasticity scale is 1 [36]. Using his approach, $\alpha+\beta+\gamma>1$ represents increasing returns to scale, $\alpha+\beta+\gamma=1$ represents constant returns to scale, and $\alpha+\beta+\gamma<1$ represents decreasing returns to scale. CEP measurements are affected by other factors such as the energy intensity (EI) and industry structure (IS). Therefore, as per Battese et al., environmental factors were introduced to explain CEP differences for DMUs [37]. Therefore, the technical non-efficiency function with influencing factors takes the form

$$u_{it} = \lambda_0 + \lambda Z_{it} + w_{it} \tag{5}$$

where, Z_{it} is the impact of the technical non-efficiency factor, also known as the environmental factor. Owing to data unavailability and the focus on factors affecting carbon emissions, six environmental factors are considered here: EI, IS, technological progress (T), economic development (ED), openness (OW), and regional difference (RD). The regional CEP model in logarithmic form is

$$\ln Y_{it} = \delta_0 + \sum_j \delta_j \ln x_{jit} + 1/2 \sum_j \sum_m \delta_{jm} \ln x_{jit} \ln x_{mit} + v_{it} - u_{it} \tag{6}$$

where, j and m represent the jth and mth input variables, respectively. When $\delta_{jm}=0$, Eq. (6) is a Cobb–Douglas production function; when $\delta_{jm} \neq 0$, Eq. (6) is the trans-log production function.

2.2. Relevant variables and data

Panel data from 1997 to 2010 for provinces in China were used to measure regional CEP. To maintain statistical integrity, data for Chongqing, a municipality directly controlled by Central Government, were merged with data for Sichuan Province. Data for the Tibet Autonomous Region and Taiwan Province could not be accessed. In accordance with traditional zoning principles, the 29 provinces, municipalities and autonomous regions were divided into three areas: Eastern, Central, and Western China. Eastern China includes 11 provinces (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan). Central China consists of eight provinces (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan). Western China comprises 10 provinces (Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang).

2.2.1. Input and output variables

The output variable is GDP, which was converted into 2000 prices using a deflator. The input variables are capital stock, labor, and CO_2 emissions. For capital stock an approach proposed by Shan was used [38], data for 2010 were developed and converted to 2000 prices. Labor was derived as the mean employed population at the end of the previous year and current years. CO_2 emissions data were calculated for final energy consumption, as recommended by IPCC. Three energy consumption indices (total coal, total oil, and natural gas) were used to determine regional CO_2 emissions according to

$$C = \sum_i a_i E_i \tag{7}$$

where, a_i is the carbon emission coefficient and E_i is the consumption for energy form i. Carbon emission coefficients for the three energy forms were taken from the literature [39–41]. The data were derived from: (1) China Energy Statistical Yearbook published by China's National Bureau of Statistics (CNBSa) [42]; and (2) China Statistical Yearbook published by China's National Bureau of Statistics (CNBSb) [43].

2.2.2. Environmental factor variables

CEP is closely related to IS because IS greatly affects the total energy consumption and per unit GDP energy consumption. IS optimization and upgrading, mainly involving a change to service-oriented tertiary industry from energy-intensive heavy industry, can promote the development of low-carbon industry and reduce carbon emissions. EI is an important indicator in measuring energy consumption efficiency, whereby a decrease in EI represents an improvement in energy efficiency and CEP. It is generally believed that CEP is highly related to the level of economic development. Besides, the higher the level of economic development, the greater total carbon emissions and per capita carbon emissions. The higher the level of economic development, the better is energy use technology, which leads to higher CEP. A remarkable feature of rapid economic development is

Table 1
Definition of the environmental factor variables[a].

Variable	Definition	Unit
Industrial structure (IS, λ_1)	Proportion of tertiary industry	%
Energy intensity (EI, λ_2)	Energy consumption/GDP	Ton standard coal per 10^4 yuan
Technological progress (T, λ_3)	Number of patent applications	Number per year
Economic development (ED, λ_4)	Per capita GDP	10^4 yuan per person
Openness (OW, λ_5)	Actual foreign investment/GDP	%
Regional difference (RD, λ_6)	Dummy variable	1 for Eastern China, 0 otherwise

[a] GDP and per capita GDP data were converted to 2000 constant prices. Data sources: China Statistical Yearbook and China Energy Statistical Yearbook.

continuous growth of foreign trade. According to IEA data, the proportion of total energy consumption for export products reached 28% in 2008. Extensive foreign trade has intensified the pressure for carbon emission reductions. However, the spillover effect for technology, equipment, and management experience arising from opening of the market will improve energy efficiency and reduce carbon emissions. CEP strongly depends on regional differences. It is reasonable to suppose that CEP is higher in developed coastal areas in Eastern China than in underdeveloped Central and Western regions.

Table 1 defines the environmental factor variables used to measure CEP based on the SFA model in this study.

3. Empirical results

Before CEP is estimated, either the Cobb–Douglas model or trans-log production function should be chosen. Since H_0:$\delta_{jm}=0$, the Cobb–Douglas production function must be used. The above assumption is tested using the generalized likelihood ratio statistic θ

$$\theta = -2\ \ln L(H_0)/L(H_1) \quad (8)$$

where, $L(H_0)$ and $L(H_1)$ are the likelihood functions for the stochastic frontier model under the null hypothesis H_0 and the alternative hypothesis H_1, respectively. If H_0 is true, the test statistic θ follows a mixed (asymptotic) χ^2 distribution with degrees of freedom corresponding to the number of bound variables. Examination reveals that θ=22.30 and the critical χ^2 distribution value is 16.81 for six degrees of freedom. Thus, H_0 is rejected and the trans-log production function must be used. Table 2 presents the maximum likelihood results.

The results in Table 2 were used to calculate the CEP for provinces in China from 1997 to 2010. Table 3 list the results.

For Figs. 1 and 2, Eastern China comprises 10 provinces, Central China, eight provinces, and Western China, 11 provinces. Thus, there are 29 provinces for all of China. Fig. 1 shows the carbon emission performance of Eastern China, Central China, Western China and China as a whole. As observed from Table 3 and Fig. 1, CEP for China gradually increased from 0.327 in 1997 to 0.615 in 2010 at an average annual growth rate of 4.97%. However, this has an upside potential of approximately 40% in quantitative form. From a regional perspective, the CEP ranking for the three major economic regions did not change during the 14-year period, with Eastern, Central, and Western China ranked in descending order. This is consistent with their energy use levels and economic development. Eastern China has the highest CO_2 emissions and the best CEP owing to its highly developed economy and effective energy utilization. In 2010, for example, the carbon EI was 2.34 t/10^4 RMB for Eastern China, 3.77 t/10^4 RMB for Central China, and 4.31 t/10^4 RMB for Western China. This ranking is consistent with the CEP results. The gap is widening over time, as exemplified by an increase in difference between Eastern China and Western China from 0.224 in 1997 to 0.430 in 2010. An upward CEP trend is evident for the provinces evaluated. Fujian had the highest CEP (0.636) in 1997, and eight provinces had CEP >0.8 in 2010. To

Table 2
Maximum likelihood estimation according to the stochastic frontier model.

Variable	Coefficient	SD	Variable	Coefficient	SD
Frontier production function estimation					
δ_0	1.314	0.602	δ_{ll}	0.025	0.033
δ_k	0.331	0.128	δ_{cc}	0.021	0.039
δ_l	−0.284	0.152	δ_{kl}	0.018	0.014
δ_c	0.707	0.160	δ_{kc}	−0.066	0.023
δ_{kk}	0.025	0.017	δ_{lc}	0.028	0.028
Influencing factors estimation					
λ_0	0.612	0.080	λ_5	0.218E−03	0.291E−03
λ_1	0.497E−03	0.180E−02	λ_6	−0.073	0.020
λ_2	0.328	0.014	σ^2	0.016	0.001
λ_3	−0.573E−05	0.244E−05	γ	0.590	0.129
λ_4	−0.241E−04	0.203E−05			
Log likelihood	286.634				
LR test error	794.016				

Table 3
CEP for provinces in China from 1997 to 2010[a].

Region	1997	2000	2005	2009	2010	Mean
Beijing	0.383	0.496	0.929	0.986	0.988	0.747
Tianjin	0.365	0.450	0.703	0.966	0.976	0.648
Hebei	0.284	0.330	0.394	0.479	0.514	0.388
Shanxi	0.122	0.144	0.216	0.293	0.332	0.201
Inner Mongolia	0.185	0.232	0.297	0.489	0.524	0.309
Liaoning	0.302	0.385	0.445	0.640	0.696	0.465
Jilin	0.221	0.312	0.378	0.537	0.564	0.381
Heilongjiang	0.293	0.357	0.426	0.474	0.511	0.409
Shanhai	0.559	0.707	0.961	0.989	0.989	0.844
Jiangsu	0.473	0.566	0.717	0.977	0.989	0.709
Zhejiang	0.509	0.584	0.759	0.962	0.984	0.732
Anhui	0.324	0.331	0.385	0.462	0.517	0.385
Fujian	0.636	0.686	0.639	0.787	0.859	0.702
Jiangxi	0.341	0.370	0.422	0.530	0.574	0.428
Shandong	0.411	0.501	0.550	0.743	0.812	0.569
Henan	0.313	0.345	0.385	0.489	0.531	0.394
Hubei	0.350	0.417	0.415	0.555	0.611	0.446
Hunan	0.343	0.456	0.399	0.540	0.602	0.449
Guangdong	0.541	0.629	0.864	0.980	0.987	0.786
Guangxi	0.378	0.390	0.425	0.512	0.546	0.441
Hainan	0.475	0.497	0.490	0.547	0.585	0.497
Sichuan	0.295	0.354	0.411	0.520	0.598	0.414
Guizhou	0.111	0.137	0.165	0.238	0.263	0.169
Yunnan	0.302	0.355	0.319	0.373	0.389	0.349
Shaanxi	0.234	0.305	0.360	0.483	0.531	0.355
Gansu	0.183	0.207	0.256	0.316	0.344	0.254
Qinghai	0.185	0.215	0.242	0.301	0.354	0.245
Ningxia	0.145	0.149	0.144	0.231	0.261	0.165
Xinjiang	0.234	0.295	0.337	0.358	0.417	0.324
Eastern China	0.449	0.530	0.677	0.823	0.853	0.644
Central China	0.288	0.341	0.378	0.485	0.530	0.387
Western China	0.225	0.264	0.296	0.382	0.423	0.303
China	0.327	0.386	0.463	0.578	0.615	0.455

[a] The values have been rounded.

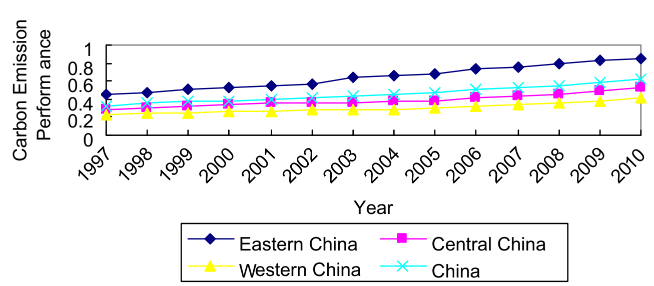

Fig. 1. Carbon emission performance in Eastern, Central, and Western China, and all of China from 1997 to 2010.

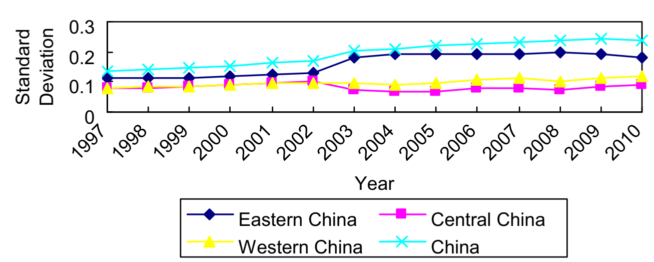

Fig. 2. Standard deviation for carbon emission performance in Eastern, Central, and Western China, and all of China from 1997 to 2010.

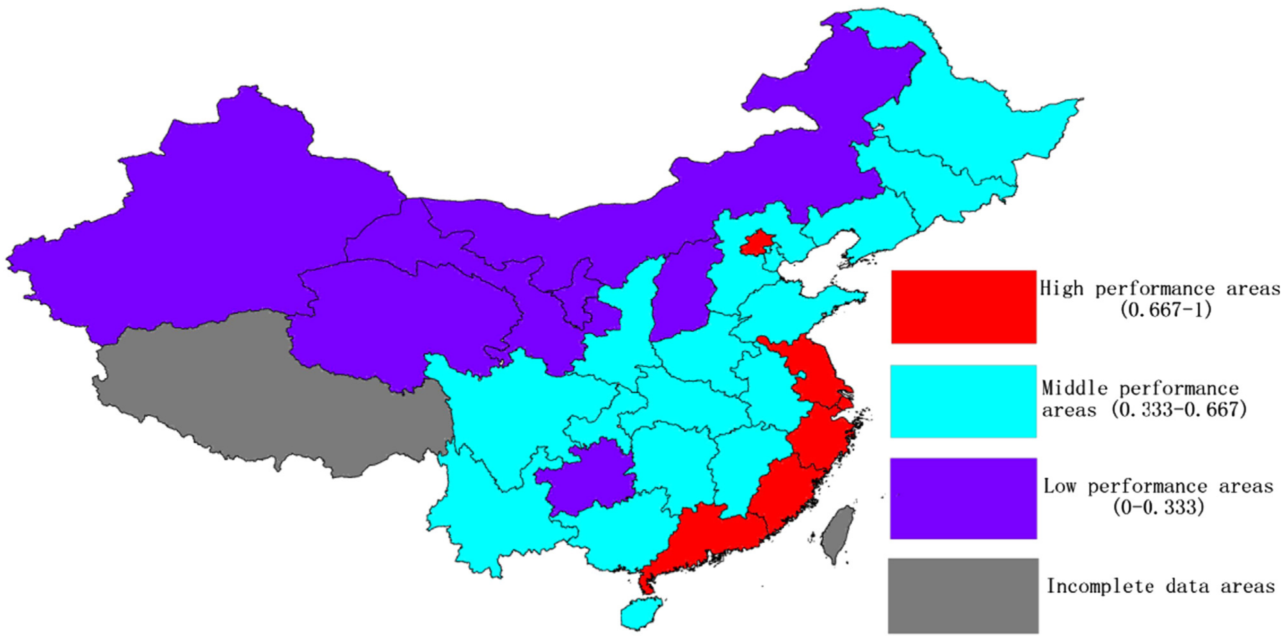

Fig. 3. Geographic distribution of the carbon emission performance in China.

Table 4
Convergence test results for carbon emission performance[a].

	Eastern China	Central China	Western China	China
C	0.0173 (0.0173)	−0.0021 (0.0010)	0.0067 (0.0221)	0.0288 (0.0081)
β	−0.0392 (0.0200)	−0.0398 (0.0075)	−0.0279 (0.0139)	−0.0173 (0.0065)
Adj-R^2	0.6207	0.7960	0.6533	0.6817
F	3.8316	28.3195	4.0528	7.2162
D.W	1.6234	2.4778	2.1634	1.3011
μ	0.0547	0.0561	0.0347	0.0197

[a] The figures in brackets represent the standard deviation (SD) of the corresponding coefficient.

show the CEP distribution more clearly, provinces are denoted as having high (CEP 0.667–1), intermediate (CEP 0.333–0.667) or low (CEP 0–0.333) efficiency in Fig. 3. The majority of the regions in China (55.2%) have intermediate carbon emission efficiency. Six provinces, located in Eastern China, have high efficiency (Shanghai, Guangdong, Beijing, Zhejiang, Jiangsu, and Fujian). Provinces with low efficiency include Ningxia, Guizhou, Shanxi, Qinghai, Gansu, Inner Mongolia, and Xinjiang. These are situated in Western China, apart from Shanxi, which is in Central China.

Analysis of the standard deviation (Fig. 2) revealed a rate of approximately 0.1 for Western China, a steady upward trend for Eastern China and all of China, and a steady downward trend for Central China. The approach of Barro and Sala-i-matin [44] was used to test the convergence or divergence of RCE performance according to the formula

$$\frac{\ln CEP_{it} - \ln CEP_{i0}}{T} = C + \beta \ln CEP_{i0} + \varepsilon \quad (9)$$

where, $\ln CEP_{i0}$ and $\ln CEP_{it}$ are the natural log of CEP at the start and at time t, respectively, and T is the time span. $\beta < 0$ corresponds to a convergence trend and $\beta > 0$ to a divergence trend for the inter-regional carbon emission performance.

$$\beta = -(1 - e^{-\mu T})/T \quad (10)$$

Eq. (10) can be used to measure the convergence or divergence speed μ for RCE performance. The results are shown in Table 4.

According to technological innovation theory, new technology penetrates new markets in three stages: invention, innovation, and diffusion. Less advanced regions can benefit from absorbing and learning technologies from more advanced regions via the diffusion effect [45]. When less advanced regions are in a more favorable position for rapid growth than more advanced regions, regional differences between them will show a convergence trend. Convergence testing shows a convergence trend for CEP both nationally and for the three major economic regions. Thus, differences among regions for CEP are narrowing. According to the convergence rate μ for RCE performance, Central China is ranked first and Western China last.

4. Conclusions

A trans-log stochastic frontier model was used to construct a model for calculating RCE performance. GDP is taken as the output variable, and capital stock, human capital, and CO_2 emissions are the variables. The influential factors include EI, IS, and other four variables. The results show that the CEP for various regions in China steadily increased from 1997 to 2010. In particular, among the three major economic regions, Eastern China is ranked first for CEP efficiency, followed by Central China and Western China. This ranking is consistent with their energy use levels and economic development. Convergence testing reveals a convergence trend for CEP both nationally and for the three major economic regions. This indicates that differences in CEP among the regions are becoming smaller.

The study results have several policy implications. The trans-log stochastic frontier model, besides economic, social, energy, and

environmental variables, includes other influential factors for measurement of RCE performance. Governments are advised to employ the newly-established model to evaluate regional CO_2 emissions status, thereby proposing effective and efficient carbon emission reduction measurements. Second, SFA efficiency estimates show that regional differences for the impact of EI, IS and other environmental factors should be considered. Overall, targeted measures are required to improve RCE performance. Third, strengthening of the market economy in China is essential. Systematic distribution of energy resources can improve the performance of each region and the nation as a whole. It is widely known that market segmentation leads to distorted allocation of resources and local protectionism induces convergence of industrial structures. These processes lead to a variety of inter-regional bottlenecks, so economies of scale do not occur and use of resources is inefficient. The fundamental solution to this problem is to foster a unified, standardized and orderly market economy to prevent widening of inter-regional differences in energy efficiency. Lastly, for rapid and sustainable economic development, the industrial structure should be adjusted by increasing the proportion of tertiary industries and decreasing the proportion of heavy industries to achieve lower EI.

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